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Evaluation of Processing Technology Reliability based on Copula-SVM

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Abstract

The inherent reliability of product was formed in design and manufacturing process, and the inherent reliability prediction model of the product is foundation of the manufacturing process control and process improvement. The method of processing technology reliability evaluation based on Copula-SVM is presented. Firstly, the principle of the inherent reliability during manufacturing process was analyzed. Secondly, the dependency structure of the process characteristic is given by means of the copula function. Finally, the inherent reliability prediction method based on support vector machine is presented, and the feasibility and practicability of the method were indicated by an industry application.

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Keywords: Inherent reliability; Prediction model; Copula—SVM; Dependency structure

1. Introduction

The product inherent reliability is decided by the design and manufacturing process. Engineering practices show that the inherent reliability of products, which are following the same design standard but manufactured by different processing methods, will have great differences[1]. Therefore, the manufacturing processes have great impacts on the product inherent reliability, and the establishment of the inherent reliability prediction model of the product is crucial to the manufacturing process control and process improvement.

Manufacturing processes are nonlinear and there is a correlation between the variables, which makes the traditional linear correlation analysis and prediction method is no longer applicable [2]. Support Vector Machine (SVM) is a machine learning algorithm, which has been used in the field of reliability evaluation and prediction. Wang [3] proposed a new method to solve the reliability prediction using weighted support vector machine to improve the standard support vector machine model.

However, process system is a complex system which is influenced by many manufacturing factors. The general support vector machine for modeling is not related to the background knowledge, domain knowledge and expert experience in manufacturing data mining, which severely degrade the efficiency and quality of data mining. With the assistance of Clayton Copula function, the dependent structure between the output of manufacturing process and influence factor can be characterized, and the dependent structure of these variables can also be used as an input of support vector machine, by which the realization of the product inherent reliability could be studied.

The infant failure rate, as an evaluation index of the inherent reliability of the process is given, and the method of processing technology reliability evaluation based on the nonlinear correlation analysis is presented. Firstly, the principle of the inherent reliability during manufacturing process was analyzed. Secondly, the dependency structure of the process characteristic is given by means of the copula function. Finally, the inherent reliability prediction method based on support vector machine is presented, and the feasibility and practicability of the method were indicated by an application case.

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2. Information Modeling of Production Process

The product reliability refers to the product properties that a system or component to perform its required functions under operational conditions for a specified period of time. Thus the operational properties of product can reflect the level of the product reliability. For example, the properties and performance wear resistance, fatigue strength and corrosion resistance have strong relationship with the product reliability. Meanwhile, the operational properties of product were decided by the output parameters of manufacturing process, such as the geometric dimensions, the surface roughness and other quality characteristics.

The current study on product process information model is focus on the integration of the product information integration of the manufacturing process, and sharing mechanism among different departments. The organization and management issues for the data and information from different sources have not been resolved. With the development of product complexity, the manufacturing data is rapid increasing, which makes the information structure can not be identified intuitively. In order to conduct logical organization and analysis for all kinds of manufacturing data, a hierarchical process information structure is needed to establish.

By analyzing the manufacturing process of the products, the production process information was classifies and organized into product layer, process layer and factor layer, as shown in Fig 1.

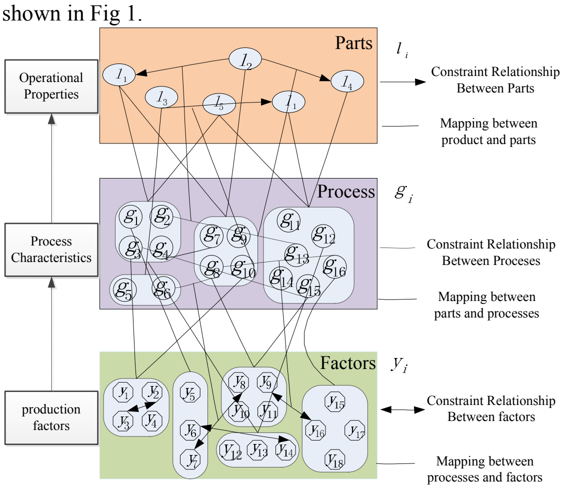

Fig.1. Dependent Structure between Manufacturing Process Factors.

Among three levels, the nodes of the product layer were constructed from parts, and the structural model is made up by the function of the parts, as well as the series and parallel relationship between the parts. The node information of the product layer include basic information about part name and number, and additional information about parts processing requirements. The nodes of process layer were constructed from process steps, and the structural model is made up by the series and parallel relationship between the process steps. The node information of process layer include basic information about step name and label, and additional information about process constraints processing conditions. The nodes of factor layer are constructed from the influencing factors during manufacture. This paper will take into account the equipment as the influencing factors to build up the model. The node information of factor layer include basic information about device name and type, and additional information about the operating parameters of the equipment.

3. Analysis of Processing technology reliability

3.1. Support Vector Machine

Support Vector Machine (SVM) is a machine learning method based on statistical learning theory, and is supervised learning model with associated learning algorithm that analyze data used for classification and regression analysis, which has the ability to deal with nonlinear regression problems using kernel function, implicitly mapping the inputs into high-dimensional feature spaces. In the specific process system environment, taking advantage of the machine learning algorithms has gained a certain results of the application in the field of reliability evaluation. SVM was proposed by Vapnik et al [5]. It uses the structural risk minimization instead of the traditional empirical risk minimization. The kernel function of the Mercer condition is used to transform the input data into the high dimensional Hilbert space, and the relationship between input and output in this space is obtained [6].

The function fitting problem of SVM [7] is as follow:

$$f(x)=(w\cdot x)+b=\sum_{i=1}^{k}(\alpha_i-\alpha_i^*)K(x\cdot x_i)+b \qquad (1)$$

Wherein, α_i, α_i^*, b in formula (1) is obtained by solving the following optimization problem, and the vector (α_i, α_i^*) is called a support vector.

$$Max: W(\alpha,\alpha^*) = -\frac{1}{2}\sum_{i,j=1}^{k}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)K(x_i\cdot x_j) + \sum_{i=1}^{k}y_i(\alpha_i-\alpha_i^*) - \varepsilon\sum_{i=1}^{k}(\alpha_i+\alpha_i^*)$$

$$\sum_{i=1}^{k}(\alpha_i-\alpha_i^*)=0, (0\le\alpha_i,\alpha_i^*\le C,\ i=1,2,\ldots,k) \qquad (2)$$

C is the penalty factor, which expressing the degree of punishment beyond the error epsilon samples, $K(x_i\cdot x_j)$is the kernel function.

3.2. Evaluation procedure based on Copula—SVM

Normalize the data (X, Y) to [0, 1], and calculate the correlation coefficient of Kendall τ of ($\bar{X}$, $\bar{Y}$) as:

$$\tau = \frac{N_c - N_d}{n(n-1)/2} \qquad (3)$$

Where N_c and N_d were expressed as the harmonious and not harmonious pairs' number. The density function of the Clayton Copula function is:

$$c(u,v,\theta) = (1+\theta)(uv)^{-\theta-1}(u^{-\theta}+v^{-\theta}-1)^{-2-\frac{1}{\theta}} \quad (4)$$

And $\theta \in (0,\infty)$ is the relevant parameter, the rank correlation coefficient τ of the relationship between θ and variable u and variable v *is*:

$$\tau = \frac{\theta}{\theta+2} \quad (5)$$

The parameter θ of the Clayton Copula can be estimated according to the Kendall τ, and then the density function c(u, v) of the Clayton Copula. And the dependent structure can be expressed by the following formula [8]:

$$\delta \approx \frac{C(u,v)}{(U+v)/2} 2C(u,v)/(u+v) \quad (6)$$

Estimated the value of δ can be expressed as:

$$F_1(x) = \frac{1}{l}\sum_{i=1}^{l}\vartheta(\bar{x}-x_i),\ \vartheta(\sigma) = \begin{cases} 1, & x>0 \\ 0, & else \end{cases} \quad (7)$$

The u is equal to $F_1(x)$ and v is equal to $F_2(y)$ under the framework of Clayton copula, and the estimation method of $F_2(y)$ is the same as $F_1(x)$. Thus the δ can be expressed as:

$$\delta \approx 2C(F_1(x), F_2(y))/(F_1(x)+F_2(y)) \quad (8)$$

Step 1: take the infant failure rate λ as the procedure of processing technology reliability evaluation, and the process characteristics were determined and expressed as x_1, x_2, … x_n through the process mechanism analysis and Failure Mode and Effect Analysis (FMEA) analysis. Collecting and collating the samples of every key process feature, for example, the samples of the first key feature are expressed as x_{1i} (i=1, 2, ⋯, z). The data of the key process characteristics under q times were collected and sorted, and δ_i (i=1, 2, ⋯, p) between process characteristic x_{i1} and process characteristic x_{i2} can be obtained according to the formula (1~9), which were shown in table 1;

Table 1. Data of inherent reliability estimation.

Process characteristics				Dependent structure				Early failure rate			
X_1	X_2	$\cdots$	X_n	δ_1	δ_2	$\cdots$	δ_p	λ_{t_1}	λ_{t_2}	$\cdots$	λ_{t_q}
x_{11}	x_{21}	$\cdots$	x_{n1}	δ_{11}	δ_{21}	$\cdots$	δ_{p1}	$\lambda_{t_1 1}$	$\lambda_{t_2 1}$	$\cdots$	$\lambda_{t_q 1}$
x_{12}	x_{22}	$\cdots$	x_{n2}	δ_{12}	δ_{22}	$\cdots$	δ_{p2}	$\lambda_{t_1 2}$	$\lambda_{t_2 2}$	$\cdots$	$\lambda_{t_q 2}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
x_{1z}	x_{2z}	$\cdots$	x_{nz}	δ_{1z}	δ_{2z}	$\cdots$	δ_{pz}	$\lambda_{t_1 z}$	$\lambda_{t_2 z}$	$\cdots$	$\lambda_{t_q z}$

Step 2: With using data mining software Clementine, take the data of the key process characteristics and the corresponding p dependent structures as the final input, and the infant failure rate data under t_i (i=1, 2, ⋯, q) as the final output. The inherent reliability prediction model can be established.

Step 3: The infant failure rate data under the new technology can be obtained through putting the data of its process characteristics into training good prediction model. And the optimal process can be selected.

4. Application

The coating process is a heat treatment which could increase the reliability of the bearing. And the process characteristics were determined and expressed as X_1 (Coating time)、X_2 (substrate bias)、X_3 (substrate temperature)、X_4 (target base distance) through the process mechanism analysis and FMEA analysis. The knowledge of the coating process and the corresponding expert experience shows that there is a coupling relationship between the two processes in the coating process, coating time and substrate temperature. Suppose that there are three different processing technologies, which are P_1, P_2, P_3, could be adopted in the coating process. The historical data of the manufacturing processes is collected in Table 2, and the data of the different processing technologies was shown in Table 3. The infant failure rate of different processing technologies and the optimal process was obtained with utilizing the proposed method.

Table 2. The manufacturing process data with input and output.

Process characteristics				Dependent structure	Early failure rate
X_1/(min)	X_2/(V)	X_3/(^{0}C)	X_4/(cm)	δ	λ_{t_0}
1500	100	450	12.5	0.321	0.25
1460	120	500	8	0.214	0.32
1420	110	453	8.5	0.25	0.36
1190	95	473	9.5	0.142	0.24
1120	105	481	9	0.452	0.21
1205	136	459	13	0.351	0.19
1290	124	495	13.5	0.312	0.23
1160	115	474	12	0.433	0.24
1365	104	463	14	0.345	0.19
1400	97	468	11.5	0.391	0.31
1026	127	471	11	0.159	0.33
1275	107	490	10	0.144	0.34
1280	131	455	10.5	0.441	0.31
1300	142	485	14.5	0.368	0.27
1340	147	507	15	0.258	0.24

Table 3. The data of the three different processing technologies.

Processing technology	Process characteristics					
	X_1/(min)	X_2/(V)	X_3/(^{0}C)	X_4/(cm)	X_5/SCCM	X_6/SCCM
P_1	1400	950	430	11.5	3.4	90
P_2	1490	150	400	9	9	165
P_3	1520	120	450	8.5	3.2	90

Step 1: δ_i (i =1,2,⋯, 15) between process characteristic coating time and process characteristic substrate temperature

can be obtained according to the formula (8), which were shown in table 2;

Step 2: take the data of the key process characteristics and the dependent structures as the final input, and the infant failure rate data which were shown as the final output. The inherent reliability prediction model was established;

Step 3: the dependence structure of the coating time and the substrate temperature of three different processing technologies were (0.231,0.252,0.243), and the infant failure rate data are calculated in combination with the data in Table 2, which is shown in Fig. 2. The infant failure rate under processing technology P_2 falls quickly in a relatively short time than process under processing technology P_1 and processing technology P_3, thus P_2 was determined as the optimal processing technology.

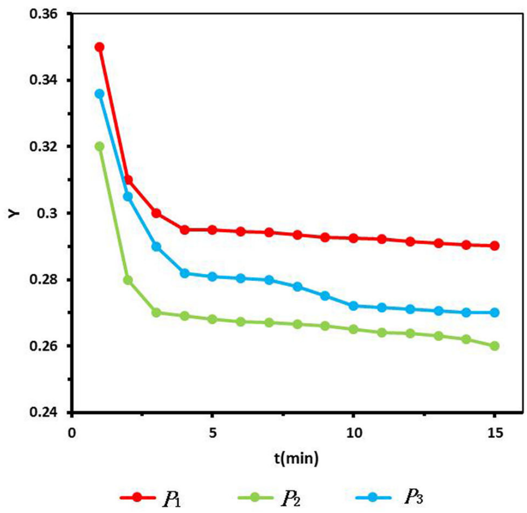

Fig. 2. Variation curves of Infant failure rate of products under different processing technologies.

5. Conclusions

The inherent reliability of product was formed during design and manufacturing process, and this paper presented a novel method for inherent reliability prediction and evaluation of the product for manufacturing process control and process improvement. The method was applied in an industry application to analyse nonlinear correlation of manufactruing process factors, where the optimal processing technology was seleceted according to the variation curves of infant failure rate of product under different processing technologies.

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